HW04WP_ML_updated

July 24, 2023

1 HW 04 Worked Problems

Purpose: For the customers of an online motorcycle clothing company, build a predictive model of Weight from a variety of body measurements plus Gender.

The data are actual body measurements of customers for a motorcycle online clothing retailer.

Data: http://web.pdx.edu/~gerbing/data/BodyMeas2500.xlsx

1.1 Preliminaries

Date of analysis

[ ]:
```
from datetime import datetime as dt
now = dt.now()
print("Analysis on", now.strftime("%Y-%m-%d"), "at", now.strftime("%H:%M %p"))
```

```
Analysis on 2023-07-24 at 14:42 PM
```

Establish current working directory

[ ]:
```
import os
os.getcwd()
```

[ ]:
```
'/Users/chasecarlson/Documents/GSCM Course Materials/GSCM 575 Machine Learning
in Business/Python Pjojects/GSCM-575-ML/code'
```

Import libraries

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
```

Import LinearRegression from sklearn and instantiate as reg_model

[ ]:
```
from sklearn.linear_model import LinearRegression
reg_model = LinearRegression()
```

1.2 1. Data Exploration and Preparation

a. Read the data.

Use read_excel to read in the data from the web.

```
[ ]: df = pd.read_excel('http://web.pdx.edu/~gerbing/data/BodyMeas2500.xlsx')
```

b. How many samples (rows of data) and columns are there in the data file?

```
[ ]: df.shape
```

```
[ ]: (2500, 7)
```

There are 2500 rows and 7 columns.

c. Display the first 5 rows of data and the variable names.

Use head() to view first few rows:

```
[ ]: df.head()
```

```
[ ]:   Gender  Weight  Height  Waist  Hips  Chest  ArmLength
     0      M     135      70     34    38     36         34
     1      M     235      66     36    45     48         32
     2      M     205      72     38    44     44         36
     3      M     190      70     36    41     40         32
     4      F     200      64     39    47     45         32
```

d. Check for missing data. Any action (deletion, imputation) needed?

After using isna().sum() to identify and count any missing data, the data set seems to be complete. No imputation required.

```
[ ]: print(df.isna().sum())
     print('Total missing: ', df.isna().sum().sum())
```

```
Gender       0
Weight       0
Height       0
Waist        0
Hips         0
Chest        0
ArmLength    0
dtype: int64
Total missing:  0
```

e. Generate a frequency distribution table of Gender.

Use value_counts() to create a frequency distribution table of Gender:

```
[ ]: df.Gender.value_counts()
```

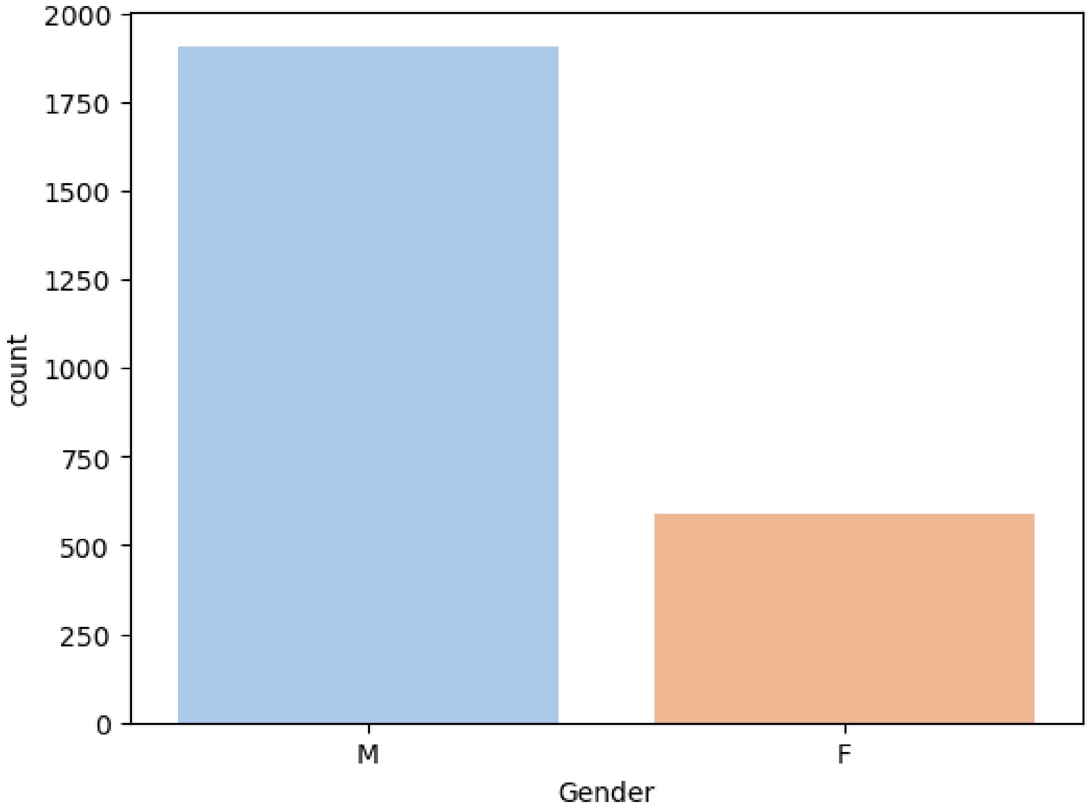
```
[ ]: M    1908
     F     592
     Name: Gender, dtype: int64
```

f. Generate a bar chart of Gender.

Use countplot() to visualize distribution of Gender:

[ ]:
```
sns.countplot(df, x = 'Gender', palette='pastel')
```

[ ]:
```
<Axes: xlabel='Gender', ylabel='count'>
```



g. Convert the two levels of Gender to two dummy variables and use one of them in the following regression analysis.

Use get_dummies() to transform Gender into two dummy variables, Gender_F and Gender_M:

[ ]:
```
df = pd.get_dummies(df, columns=['Gender'])
df.head()
```

[ ]:

	Weight	Height	Waist	Hips	Chest	ArmLength	Gender_F	Gender_M
0	135	70	34	38	36	34	0	1
1	235	66	36	45	48	32	0	1
2	205	72	38	44	44	36	0	1
3	190	70	36	41	40	32	0	1
4	200	64	39	47	45	32	1	0

1.3 2. Regression Analysis

a. Store the features, the predictor variables, in data structure X. Store the target variable in data structure y.

Isolate predictor variables and insert into data structure X. Store target variable Weight into data structure y:

[ ]:
```
pred_vars = ['Height', 'Waist', 'Hips', 'Chest', 'ArmLength', 'Gender_M']
X = df[pred_vars]
y = df['Weight']
```

b. Use code to display the number of features.

Use len() to count the number of feature variables:

[ ]:
```
n_pred = len(pred_vars)
print("Number of predictor variables: ", n_pred)
```

```
Number of predictor variables:  6
```

c. Split the data into 75% training data and 25% testing data.

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=.25,
                                                    random_state=1)
```

Confirm it worked properly by viewing the shape of the test & train data structures.

[ ]:
```
print("Shape of X data structures: ", X_train.shape, X_test.shape)
print("Shape of y data structures: ", y_train.shape, y_test.shape)
```

```
Shape of X data structures:  (1875, 6) (625, 6)
Shape of y data structures:  (1875,) (625,)
```

d. Do the multiple regression with all possible features. Display the estimated model coefficients.

Apply the fit() function for linear regression:

[ ]:
```
reg_model.fit(X_train, y_train)
```

[ ]:
```
LinearRegression()
```

Calculate the y-intercept and coefficients for training data:

[ ]:
```
print('intercept: %3f' % (reg_model.intercept_), '\n')

cdf = pd.DataFrame(reg_model.coef_, X.columns, columns=['Coefficients'])
print(cdf)
```

```
intercept: -331.629500
```

```
            Coefficients
Height          2.802635
Waist           1.923748
Hips            2.137972
Chest           3.353648
ArmLength       0.359313
Gender_M        6.508491
```

e. For the person who provided the first row of data, manually calculate his fitted weight from the model explicitly from the model coefficients. (For pedagogy, to show understanding of the model, not normally done here.)

View the first few rows of predictor variables for reference:

[ ]:
```
X.head()
```

[ ]:

	Height	Waist	Hips	Chest	ArmLength	Gender_M
0	70	34	38	36	34	1
1	66	36	45	48	32	1
2	72	38	44	44	36	1
3	70	36	41	40	32	1
4	64	39	47	45	32	0

Store feature values and coefficients in variables to use in multiple regression equation:

[ ]:
```
intercept = reg_model.intercept_

b_height = X.loc[0, 'Height']
x_height = cdf.loc['Height', 'Coefficients']
b_waist = X.loc[0, 'Waist']
x_waist = cdf.loc['Waist', 'Coefficients']
b_hips = X.loc[0, 'Hips']
x_hips = cdf.loc['Hips', 'Coefficients']
b_chest = X.loc[0, 'Chest']
x_chest = cdf.loc['Chest', 'Coefficients']
b_arm = X.loc[0, 'ArmLength']
x_arm = cdf.loc['ArmLength', 'Coefficients']
b_gender = X.loc[0, 'Gender_M']
x_gender = cdf.loc['Gender_M', 'Coefficients']
```

Apply to multiple regression formula:

[ ]:
```
fitted_weight = intercept + (b_height * x_height) + (b_waist * x_waist) +
 ↪(b_hips * x_hips) + (b_chest * x_chest) + (b_arm * x_arm) + (b_gender *
 ↪x_gender)
print("Predicted weight for first row: ", fitted_weight)
```

```
Predicted weight for first row:  150.66179903202556
```

OR insert values manually:

```
[ ]: fitted_weight2 = -331.629500 + (2.802635 * 70) + (1.923748 * 34) + (2.137972 *␣
     ↪38) + (3.353648 * 36) + (0.359313 * 34) + (6.508491 * 1)
     print("The fitted weight of the person in the first row is: ", fitted_weight2,␣
     ↪"lbs")
```

```
The fitted weight of the person in the first row is:  150.661779 lbs
```

f. What is the residual for the first person? Comment.

Formula to calculate residual: e = $y_i - \hat{y}_i$

```
[ ]: # df.loc[0, 'weight'] identifies the first row of the Weight column of the␣
     ↪original data frame.
     # fitted_weight2 represents the predicted weight from the previous calculation.
     e = df.loc[0, 'Weight'] - fitted_weight2
     e
```

```
[ ]: -15.661778999999996
```

The residual for the person in the first row is -15.661778999999996. This means that the predicted value was approximately -15.66 pounds different than the actual weight of the person in the first row.

g. Compute the forecasted values of y, $\hat{y}$, from the testing data for X.

y_fit calculates $\hat{y}$ when the model is applied (fitted) to the training data, and y_pred calculates $\hat{y}$ when the model is applied to the test data.

```
[ ]: y_fit = reg_model.predict(X_train)
     y_pred = reg_model.predict(X_test)

     print(pd.DataFrame(reg_model.predict(X_train)))
     print(pd.DataFrame(reg_model.predict(X_test)))
```

```
               0
0     154.798121
1     176.475776
2     180.721586
3     108.955845
4     112.281111
…            …
1870  140.137094
1871  177.299138
1872  214.034495
1873  172.652367
1874  206.913923

[1875 rows x 1 columns]
              0
0    138.684670
1    183.317607
```

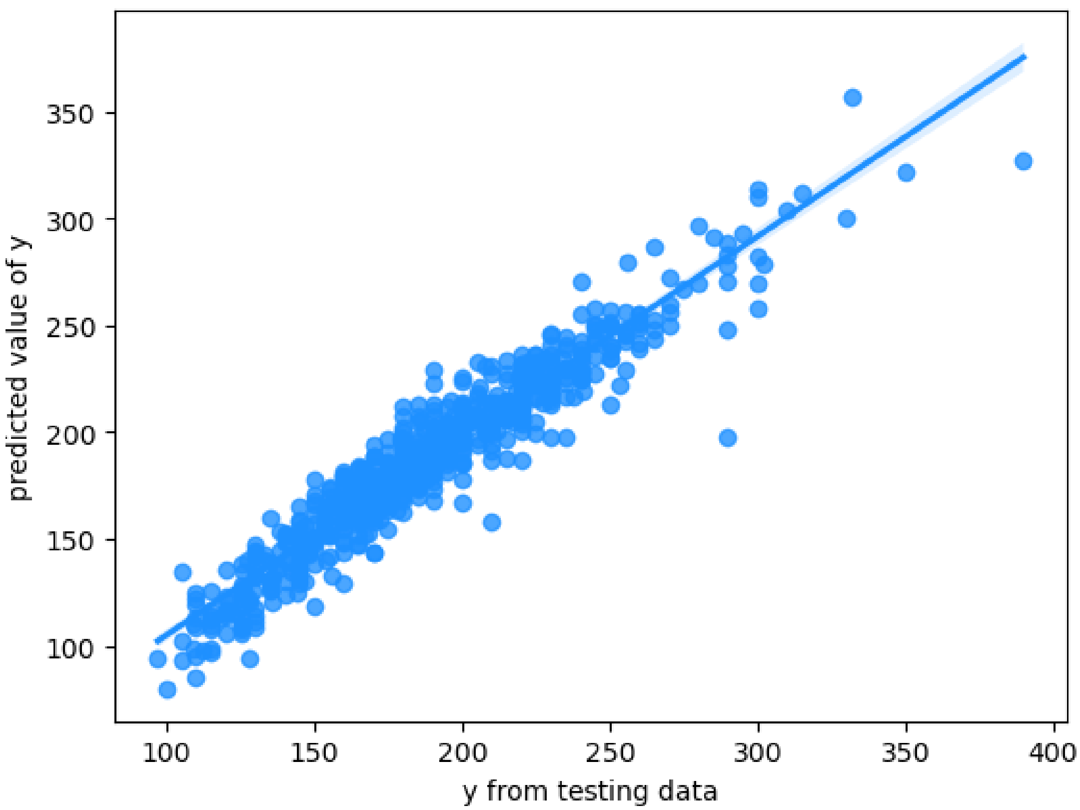
```
2     249.451167
3     224.727100
4     157.158072
..           …
620   207.691352
621   138.067944
622   123.468895
623   157.728408
624   311.558153

[625 rows x 1 columns]
```

h. Visually compare the forecasted values of y from the model applied to the testing data to the obtained values of y in the testing data. Comment

Use regplot() to create a scatterplot with regression line for visual assessment of residuals.

[ ]:
```python
ax = sns.regplot(x=y_test, y=y_pred, color='dodgerblue')
ax.set(xlabel='y from testing data', ylabel='predicted value of y')
```

[ ]:
```
[Text(0.5, 0, 'y from testing data'), Text(0, 0.5, 'predicted value of y')]
```



i. Evaluate model fit to the training data with the standard deviation of residuals and

R-squared. Comment

The R-squared value for the test data is very high, at 0.887, which means that the model is a good fit for the test data with the applied variables, however, we will need to see the performance against the test data to determine whether the model is a good fit for the overall data set or not.

```
[ ]: from sklearn.metrics import mean_squared_error, r2_score
     mse = mean_squared_error(y_train, y_fit)
     rsq = r2_score(y_train, y_fit)
     print("MSE: %.3f" % mse)
     se = np.sqrt(mse)
     range95 = 4 * se
     print("Stdev of residuals: %.3f " % se)
     print("R-squared: %.3f" % rsq)
```

```
MSE: 224.515
Stdev of residuals: 14.984
R-squared: 0.887
```

j. Evaluate model fit to the testing data with the standard deviation of residuals and R-squared. Comment

The standard deviation of the residuals drops from 14.984 to 13.326, and R-squared improved from 0.887 to 0.909 when the model applied to the test data. This validates that the model is still a good fit.

```
[ ]: mse_f = mean_squared_error(y_test, y_pred)
     rsq_f = r2_score(y_test, y_pred)
     print('Forecasting Mean squared error: %.3f' % mse_f)
     print('Forecasting Standard deviation of residuals: %.3f' % np.sqrt(mse_f))
     print('Forecasting R-squared: %.3f' % rsq_f)
```

```
Forecasting Mean squared error: 177.588
Forecasting Standard deviation of residuals: 13.326
Forecasting R-squared: 0.909
```

k. Is the model overfit?

The model is not overfit because it performed just as good or better when applied to the testing data.

l. Cross-validate the data with five randomly selected folds, and evaluate with the average value of the standard deviation of residuals and R-squared across the folds.

Import KFold from sklearn.model_selection and split the data into 5 folds

```
[ ]: from sklearn.model_selection import KFold, cross_validate
     # instantiate the KFold model with 5 splits, shuffle the data prior to split,␣
      ↪and set the seed to recover same set in future.
     kf = KFold(n_splits=5, shuffle=True, random_state=1)
```

Calculate scores for each fold

[ ]:
```
scores = cross_validate(reg_model, X, y, cv=kf,
                        scoring=('r2', 'neg_mean_squared_error'),
                        return_train_score=True)
```

Convert scores to data frame

[ ]:
```
ds = pd.DataFrame(scores)
ds.head()
```

[ ]:
```
   fit_time  score_time   test_r2  train_r2  test_neg_mean_squared_error  \
0  0.001917    0.000554  0.899467  0.890679                  -183.506873
1  0.000967    0.000469  0.904874  0.889601                  -174.515332
2  0.000826    0.000451  0.830941  0.909158                  -359.182597
3  0.000816    0.000455  0.905171  0.889231                  -184.512008
4  0.003115    0.001220  0.920204  0.884657                  -171.481808

   train_neg_mean_squared_error
0                   -220.196742
1                   -222.249204
2                   -176.276181
3                   -219.900832
4                   -223.071235
```

Rename MSE columns and convert to positive values:

[ ]:
```
ds.rename(columns = {'test_neg_mean_squared_error': 'test_MSE',
                     'train_neg_mean_squared_error': 'train_MSE'},
                     inplace=True)

ds['test_MSE'] = -ds['test_MSE']
ds['train_MSE'] = -ds['train_MSE']

print(ds.round(4))
```

```
   fit_time  score_time  test_r2  train_r2  test_MSE  train_MSE
0    0.0019      0.0006   0.8995    0.8907  183.5069   220.1967
1    0.0010      0.0005   0.9049    0.8896  174.5153   222.2492
2    0.0008      0.0005   0.8309    0.9092  359.1826   176.2762
3    0.0008      0.0005   0.9052    0.8892  184.5120   219.9008
4    0.0031      0.0012   0.9202    0.8847  171.4818   223.0712
```

Calculate average R-squared value and standard deviation across all 5 folds

[ ]:
```
print('Mean of test R-squared scores: %.3f' % ds['test_r2'].mean())
print('Mean of test MSE scores: %.3f' % ds['test_MSE'].mean())
se = np.sqrt(ds['test_MSE'].mean())
print('Standard deviation of mean test MSE scores: %.3f' % se)
```

```
Mean of test R-squared scores: 0.892
Mean of test MSE scores: 214.640
```

```
Standard deviation of mean test MSE scores: 14.651
```

The average R-squared value remains consistent at 0.892, slightly lower than when applied to the single test set, but not a significant change.

1.4 3. Feature Selection

Can we obtain the same level of forecasting accuracy with a smaller set of features?

a. Show uniqueness and relevance of each feature in a single table that consists of VIFs and target correlations. Comment.

Create a new data frame and add columns for Predictor names, VIF, and Relevance.

```
[ ]: from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Predictor'] = X.columns
# Uses loop to calculate VIF for each variable in the X data structure
vif['VIF'] = [variance_inflation_factor(X.values, i)
for i in range(X.shape[1])]
# Calculate the correlation between predictor variables and target variable␣
 ↪'Weight'
cr = df.corr()['Weight'].round(3)
# Uses loop to assign correlation values to the Relevance column for each␣
 ↪variable.
vif['Relevance'] = [cr[i]
for i in range(X.shape[1])]

vif
```

[ ]:

	Predictor	VIF	Relevance
0	Height	419.131300	1.000
1	Waist	216.931126	0.622
2	Hips	331.700435	0.861
3	Chest	295.719089	0.782
4	ArmLength	394.445013	0.876
5	Gender_M	6.261650	0.593

VIF factors are high for all variables except for gender, indicating there is a strong correlation between predictor variables in the data set.

b. Run the multivariate feature selection algorithm to retain the top three features.

```
[ ]: from sklearn.linear_model import LinearRegression
estimator = LinearRegression()
from sklearn.feature_selection import RFE
selector = RFE(estimator, n_features_to_select=3, step=1).fit(X,y)
```

View which variables were selected as best:

[ ]:
```
print(selector.support_)
print(selector.ranking_)
```

```
[False False  True  True False  True]
[2 3 1 1 4 1]
```

c. Subset a new data frame of the feature variables that contains just these three predictors. Call it X2. Show the first several rows of data.

Use the support_ output structure from RFE(). Subset the data with iloc() to redefine the feature data frame.

[ ]:
```
X2 = X.iloc[:, selector.support_]
X2.head()
```

[ ]:

	Hips	Chest	Gender_M
0	38	36	1
1	45	48	1
2	44	44	1
3	41	40	1
4	47	45	0

d. Now fit this reduced model to all the data, X2 and y. Then generate the predicted scores into a data structure named y_fit2.

Reestablish 'Weight' column as our target variable, y and assign the three predictor variables to X2.

[ ]:
```
y = df['Weight']
pred_vars2 = ['Hips', 'Chest', 'Gender_M']
X2 = df[pred_vars2]
```

[ ]:
```
reg_model.fit(X2, y)
```

[ ]:
```
LinearRegression()
```

Check the coefficients with the new predictor variables:

[ ]:
```
print("intercept: %.3f" % (reg_model.intercept_), "\n")
cdf = pd.DataFrame(reg_model.coef_, X2.columns, columns=['Coefficients'])
print(cdf)
```

```
intercept: -182.426

          Coefficients
Hips          3.474910
Chest         4.786842
Gender_M     23.485107
```

Generate forecasts

[ ]:
```
y_fit2 = reg_model.predict(X2)
```

Put coefficients from 'before' and 'after' feature selection into its own data frame for comparison:

```
[ ]: pd.DataFrame({'Feature': ['Hips', 'Chest', 'Gender_M'], 'Before': [2.137972, 3.
     ↪353648, 6.508491], 'After': [3.474910, 4.786842, 23.485107]})
```

```
[ ]:     Feature    Before      After
     0      Hips  2.137972   3.474910
     1     Chest  3.353648   4.786842
     2  Gender_M  6.508491  23.485107
```

Coefficients increased for each variable, particularly Gender_M which increased from 6.5 to 23.485.

e. Did fit suffer from reducing the number of features from 5 to 3? Comment.

Run the fit metrics using y_fit2 to determine how fit was impacted by removing predictor variables:

```
[ ]: from sklearn.metrics import mean_squared_error, r2_score
     mse = mean_squared_error(y, y_fit2)
     rsq = r2_score(y, y_fit2)
     print("MSE: %.3f" % mse)
     se = np.sqrt(mse)
     print("Stdev of residuals: %.3f " % se)
     print("R-squared: %.3f" % rsq)
```

```
MSE: 316.030
Stdev of residuals: 17.777
R-squared: 0.840
```

Stdev of residuals increased from 14.984 to 17.777, and R-squared reduced from 0.887 to 0.840, suggesting slightly poorer fit with the new features.

Recalculate the variance inflation factors and relevance for the predictor variables:

```
[ ]: vif = pd.DataFrame()
     vif['Predictor'] = X2.columns
     vif['VIF'] = [variance_inflation_factor(X2.values, i)
     for i in range(X2.shape[1])]
     cr = df.corr()['Weight'].round(3)
     vif['Relevance'] = [cr[i]
     for i in range(X2.shape[1])]
     vif
```

```
[ ]:   Predictor         VIF  Relevance
     0      Hips  192.682979      1.000
     1     Chest  213.759829      0.622
     2  Gender_M    5.277822      0.861
```

Variance inflation vactors dropped for each variable compared to the original model. We successfully reduced collinearity in the data, but the overall results from the model did not improve.